## shape\_statistic

## December 1, 2021

Implement metrics to compare two arbitrary distributions and apply to velocity profiles. Check the implementations for similarity by eye At the end we can add the velocity distribution similarity metric to our analysis (e.g. sobolnote.py)

```
[15]: import sys, os
    join = lambda *x: os.path.abspath(os.path.join(*x))
    import numpy as np
    import matplotlib.pyplot as plt
    import pili
    import rtw
    import plotutils
    import collections
    import scipy.stats
    import pandas as pd
    import parameters
    import seaborn as sns
```

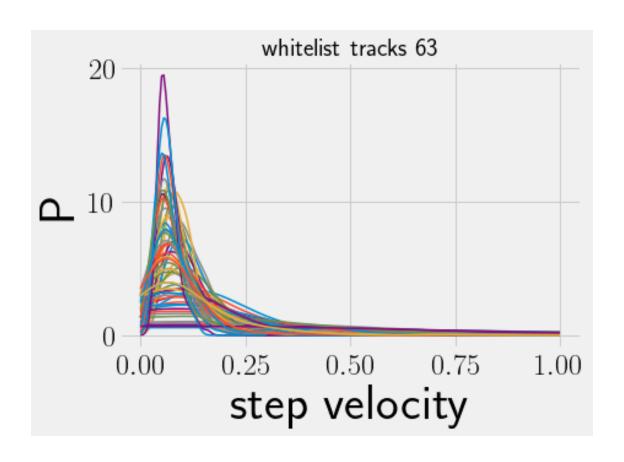
```
[16]: # paths
    notedir, notename = os.path.split(os.getcwd())
    notedir, notename
    root = pili.root
    # candidate to compare against
    print("loading experiment data")
    all_idx, all_trs = _fj.slicehelper.load_linearized_trs("all")
    flipped, scores = _fj.redefine_poles(all_trs)
    reference_idx = _fj.load_subset_idx()
    reftrs = {}
    for key, subidx in reference_idx.items():
        reftrs[key] = [all_trs[idx] for idx in subidx]

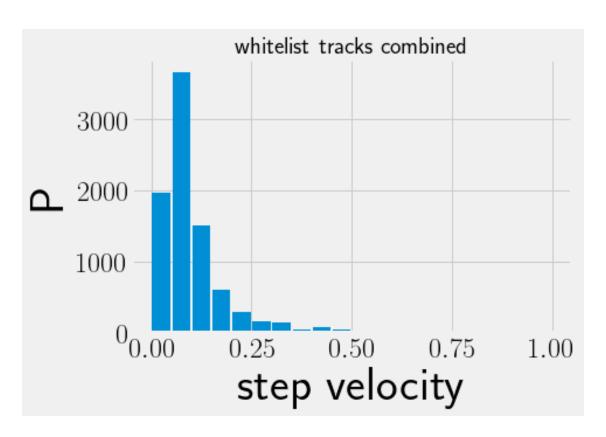
    print("finished")
```

```
10%| | 298/3113 [00:00<00:00, 2972.37it/s]
```

loading experiment data

```
| 3113/3113 [00:01<00:00, 2142.74it/s]
     /home/dan/.local/lib/python3.8/site-packages/numpy/core/fromnumeric.py:3419:
     RuntimeWarning: Mean of empty slice.
       return _methods._mean(a, axis=axis, dtype=dtype,
     /home/dan/.local/lib/python3.8/site-packages/numpy/core/ methods.py:188:
     RuntimeWarning: invalid value encountered in double_scalars
       ret = ret.dtype.type(ret / rcount)
     flipped 631/3113 tracks (20.3%)
     finished
[17]: # simulation
      angle1d_dir = join(root, "../run/new/angle_smoothed/range_pbrf")
      simdata = collections.OrderedDict()
      simdata[angle1d_dir] = rtw.DataCube(target=angle1d_dir)
[18]: # config
      histstyle = {'rwidth': 0.9}
[19]: # plot individual track and combined distributions
      fig,ax = plt.subplots(figsize=(6,4))
      vellst = ∏
      xlim = (0,1.0)
      ax.set_title("whitelist tracks {}".format(len(reftrs["top"])))
      for tr in reftrs["top"]:
          vel = tr.get step speed()
          vellst.append(_vel)
          plotutils.ax kdeplot(ax, vel, xlims=xlim)
          ax.set_xlabel("step velocity")
          ax.set_ylabel("P")
      fig,ax = plt.subplots(figsize=(6,4))
      ax.set_title("whitelist tracks combined")
      ref_vel = np.concatenate(vellst)
      ax.hist(ref_vel, bins=20, range=xlim, **histstyle)
      ax.set_xlabel("step velocity")
      ax.set_ylabel("P")
      plt.show()
```



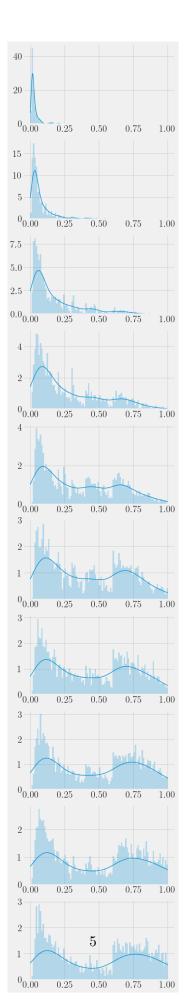


```
[20]: # plot velocity distributions for this 1d search
      import readtrack
      dc = list(simdata.values())[0]
      print(str(dc))
      trdata = dc.autocalculate(readtrack.trackset)
      trdata = [[_fj.linearize(tr) for tr in trs] for trs in trdata]
      vel = [np.concatenate([tr.get_step_speed() for tr in trs]) for trs in trdata]
      nsteps = [np.sum([len(tr.step_idx) for tr in trs]) for trs in trdata]
      print("nsteps", nsteps)
      basis = dc.basis[0]
      n = len(basis)
      fig, axes = plt.subplots(n, figsize=(6,n*4))
      # for i, value in list(enumerate(basis))[3:]:
      for i, ax in enumerate(axes):
          plotutils.ax_kdeplot(ax, vel[i], xlims=xlim ,hist=True)
     DataCube inspected directories at -->
     /home/dan/usb_twitching/run/new/angle_smoothed/range_pbrf
     parameters: ['anchor_angle_smoothing_fraction']
     with shape: [10]
     with basis:
```

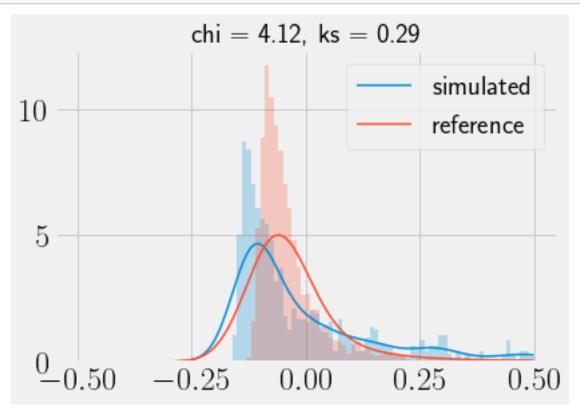
anchor\_angle\_smoothing\_fraction = [0.031, 0.062, 0.125, 0.25, 0.375, 0.5, 0.625,

nsteps [284, 519, 962, 1467, 1958, 2342, 2537, 2658, 2671, 2702]

0.75, 0.875, 1.0]

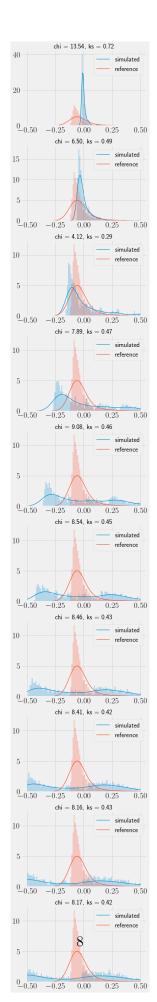


```
[21]: # superimise one simulated trajectory with the reference data
      # def mean(x): return scipy.stats.trim_mean(x, 0.025)
      mean = np.mean
      def plot_similarity(ax, sim_vel, ref_vel):
          v1 = sim_vel - mean(sim_vel)
          v2 = ref_vel - mean(ref_vel)
          show_hist = True
          plotutils.ax_kdeplot(ax, v1, xlims=(-0.5,0.5), hist=show_hist)
          plotutils.ax_kdeplot(ax, v2, xlims=(-0.5,0.5), hist=show_hist)
          ax.legend(["simulated", "reference"])
          ks_statistic, pvalue = scipy.stats.ks_2samp(v1, v2)
          chi = twanalyse.chisquare(v1, v2)
          ax.set_title("chi = {:.2f}, ks = {:.2f}".format(chi, ks_statistic))
      # test
      i = 2
      fig, ax = plt.subplots(figsize=(6,4))
      plot_similarity(ax, vel[i], ref_vel)
```



```
[22]: # superimpose simulated data on reference data for the whole 1d range

n = len(basis)
fig, axes = plt.subplots(n, figsize=(6,n*4))
# for i, value in list(enumerate(basis))[3:]:
for i, ax in enumerate(axes):
    plot_similarity(ax, vel[i], ref_vel)
plt.tight_layout()
```



If we need a reference for what these similarity numbers actually mean we can check back on this notebook We should be ready to add these metrics to our summary statistics

```
[23]: # switch over to searching sobol dataset for the closest examples
      import sobol
      import twutils
      simdir = "/home/dan/usb_twitching/run/b2392cf/cluster/sobol_01"
      lookup = sobol.read_lookup(simdir)
      problem = sobol.read_problem(simdir)
      twutils.print_dict(problem)
      _ , lduid = sobol.collect([], targetdir=simdir, alldata=True)
     {
              "num_vars": 6,
              "names": [
                      "k_ext_off",
                      "dwell_time",
                      "pilivar",
                      "anchor_angle_smoothing_fraction",
                      "k_spawn",
                      "k_resample"
             ],
              "bounds": [
                      Γ
                              0.2,
                              1.0
                      ],
                      Γ
                              0.5,
                              3.0
                      ],
                      1.0,
                              20.0
                      ],
                      Γ
                              0.125,
                              1.0
                      ],
                      0.5,
                              5.0
                      ],
                              1.0,
```

```
10.0
                     ]
             ]
     }
[24]: # load exp data
      def _load_subset_speed():
          distrib = {}
          for name, ltrs in _fj.load_subsets().items():
              distrib[name] = np.concatenate([ltr.get_step_speed() for ltr in ltrs])
          return distrib
      ref_vel = _load_subset_speed()
                | 1/1 [00:00<00:00, 2898.62it/s]
     100%|
                | 63/63 [00:00<00:00, 6450.57it/s]
     100%
               | 81/81 [00:00<00:00, 3940.09it/s]
     100%|
               | 79/79 [00:00<00:00, 1849.41it/s]
     100%
     100%|
                | 175/175 [00:00<00:00, 5294.04it/s]
[25]: subsets = reference_idx.keys()
      # scores = ['fanjin.%s.chi' % subset for subset in reference_idx.keys()]
      scores = ['fanjin.%s.ks_statistic' % subset for subset in reference_idx.keys()]
      Yf = sobol.collect obs(lookup, lduid, subsets, scores)
      def sortscore(problem, lookup, Yf, scores):
          # need to sort each column seperately, can't do this in one dataframe
          # construct a dataframe with cols [i, simulation_index, score] for each_
       \rightarrow subset
          paramlist = problem["names"]
          sortdf = {}
          for subset, data in Yf.items():
              sortidx = np.argsort(data)
              udir = [lookup[0][idx] for idx in sortidx]
              _cols = {"index": sortidx, "dir": udir, "score": data[sortidx]}
              _parlist = zip(problem["names"], zip(*[lookup[1][_u] for _u in udir]))
              _cols.update({k:v for k, v in _parlist})
              _df = pd.DataFrame(_cols)
              sortdf[subset] = df
          return sortdf
      sortdf = sortscore(problem, lookup, Yf, scores)
      sortdf["top"]
[25]:
             index
                                    score k_ext_off dwell_time
                                                                     pilivar \
                            dir
      0
              5599 _u_4BvpMFSM 0.119646
                                            0.451563
                                                        1.012695
                                                                    1.185547
      1
              5490 _u_bjwAuQOL
                                 0.125704
                                                        1.950195
                                                                    2.669922
                                            0.357813
                   _u_cEN2qG75 0.126801
      2
              5618
                                            0.682813
                                                        2.555664
                                                                    3.263672
      3
              9935
                   _u_mcOorhHg 0.127497
                                            0.232031
                                                        1.767090
                                                                    6.733398
```

0.250781

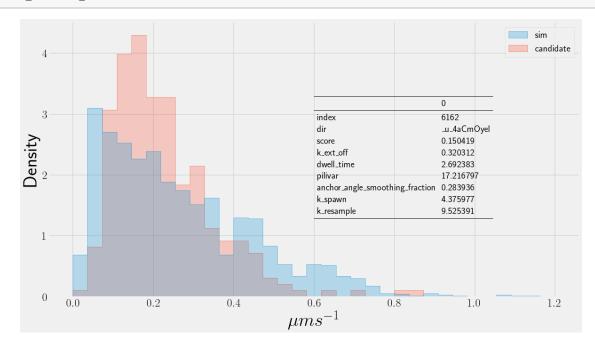
1.488770 13.747070

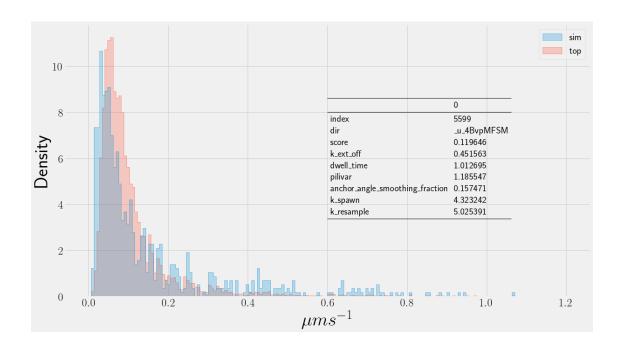
9164

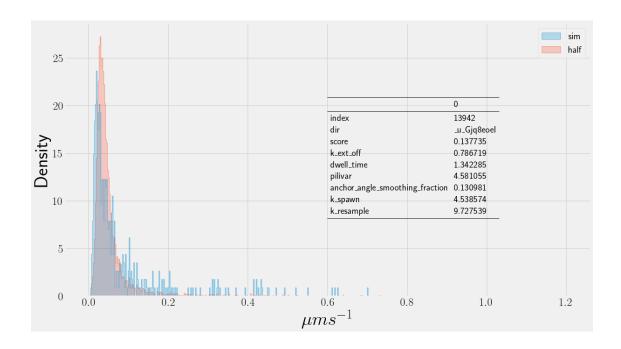
\_u\_7yd0LsJx 0.131379

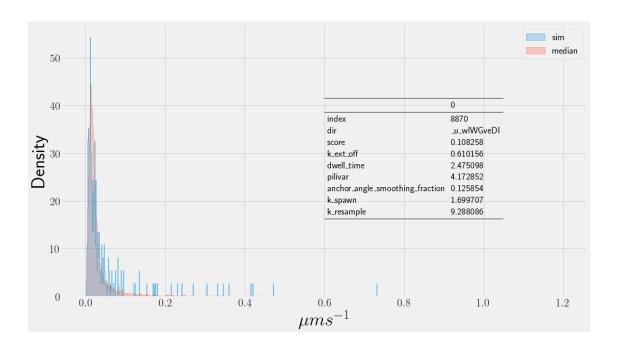
```
5 _u_SyQdaakH 0.819537
      14331
                                           0.200000
                                                       0.500000
                                                                  1.000000
      14332
              751 _u_GM4vF92B 0.820310
                                           0.712500
                                                       0.695312 18.515625
            11728 _u_1179ubjo 0.822192
      14333
                                           0.633594
                                                       2.738770 19.350586
      14334
                7 _u_L9q4zFIY 0.840073
                                           0.200000
                                                       0.500000
                                                                  1.000000
                2 _u_Af99lwPr 0.852711
      14335
                                           0.200000
                                                       0.500000
                                                                  1.000000
            anchor_angle_smoothing_fraction
                                              k_spawn k_resample
                                                         5.025391
      0
                                   0.157471 4.323242
      1
                                   0.160889 3.602539
                                                         9.103516
                                   0.184814 4.586914
      2
                                                         8.259766
      3
                                   0.142944 4.248535
                                                         7.565430
                                   0.163452 4.283691
                                                         8.338867
      14331
                                   0.125000 0.500000 1.000000
                                   0.138672 0.992188
      14332
                                                         5.359375
      14333
                                   0.125854 1.005371
                                                         9.727539
      14334
                                   0.125000 0.500000
                                                         1.000000
      14335
                                   0.125000 0.500000
                                                         1.000000
      [14336 rows x 9 columns]
[26]: # sync target data from cluster here in notebook
      from sobol import sync_directory
      best = sortdf["top"].iloc[0]
[27]: mpl.rcParams["text.latex.preamble"] = r'\usepackage{booktabs}'
      histstyle = {"stat":"density", "common_norm": False, "element":"step"}
      def plot superimposed(dfrow, subset, simdir, histstyle=histstyle):
         target = join(simdir, dfrow["dir"])
          if not os.path.exists(join(target, "data/")):
              output = sync_directory(target)
         ltrs = twanalyse.get_linearised_data(ddir=target)
         lvel = np.concatenate([ltr.get_step_speed() for ltr in ltrs])
         xlim = (0, 1.2)
         data = {"sim": lvel, subset: ref_vel[subset]}
         fig, ax = plt.subplots()
         sns.histplot(data, binrange=xlim, ax=ax, **histstyle)
         ax.text(.5,.5, dfrow.to latex().replace('\n', ''),
             transform=ax.transAxes, fontsize=20)
         ax.set xlabel("$\mu ms^{-1}$")
         return ax
      def plot_subset_best(sortdf, simdir):
         for subset in sortdf.keys():
              i = 0
             best = sortdf[subset].iloc[i]
```

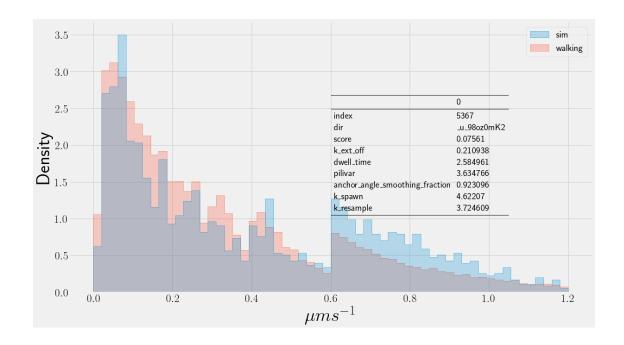
## [28]: plot\_subset\_best(sortdf, simdir)











```
[29]: use_chi = False
if use_chi:
    chi_scores = ['fanjin.%s.chi' % subset for subset in reference_idx.keys()]
    chi_Yf = sobol.collect_obs(lookup, lduid, subsets, chi_scores)
    chi_sortdf = sortscore(problem, lookup, chi_Yf, chi_scores)
    chi_sortdf["candidate"]
[30]: if use chi:
```

```
[30]: if use_chi: plot_subset_best(chi_sortdf, simdir)
```

```
[31]: # It's clear our chi similarity totally fails for "top" and "candidate"
    # but we know better matches exist because the ks_statistic works much better
    import scipy.stats
    check_chi = False
    if check_chi:
        _best = chi_sortdf["top"].iloc[0]
        res = 100
        ltrs = twanalyse.get_linearised_data(ddir=join(simdir, _best["dir"]))
        lvel = np.concatenate([ltr.get_step_speed() for ltr in ltrs])
        ref = ref_vel["top"]
```

```
[32]: if check_chi:
    v1 = lvel - np.mean(lvel)
    v2 = ref - np.mean(ref)
    print("mean", np.mean(lvel), np.mean(ref))
    _q = 0.050 # vary this
    xn1, xm1 = np.quantile(v1, _q), np.quantile(v1, 1.0 - _q)
```

```
xn2, xm2 = np.quantile(v2, _q), np.quantile(v2, 1.0 - _q)
xn, xm = min(xn1, xn2), max(xm1, xm2)
print(xn1, xm1)
print(xn2, xm2)
print("xlims", xn, xm)
mspace = np.linspace(xn, xm, res)
# method = "scott"
def method(self):
   div f = 4.0 # vary this
   return np.power(self.neff, -1./(self.d+4)) / div_f
kde1 = scipy.stats.gaussian kde(v1, bw method=method)
kde2 = scipy.stats.gaussian_kde(v2, bw_method=method)
pde1 = kde1.evaluate(mspace)
pde2 = kde2.evaluate(mspace)
plt.plot(mspace, pde1, label="")
plt.plot(mspace, pde2)
chisquared = np.sum((pde2 - pde1)**2/(pde1 + pde2))
print("chi", np.sqrt(chisquared))
fig, ax = plt.subplots()
sns.histplot({"sim":v1, "top":v2}, binrange=(xn, xm), **histstyle)
```

the chi metric is failing because the bandwidth is too large reducing by a factor 4 works well for this example but it may make the other examples worse (?) until we can figure out a more robust method, put trust in ks\_statistic instead

```
[33]: simdir = "/home/dan/usb_twitching/run/5bfc8b9/cluster/sobol_walking"
      lookup = sobol.read_lookup(simdir)
      problem = sobol.read_problem(simdir)
      print(problem)
      _ , lduid = sobol.collect([], targetdir=simdir, alldata=True)
     {'num_vars': 5, 'names': ['k_ext_off', 'dwell_time', 'pilivar',
     'anchor_angle_smoothing_fraction', 'k_spawn'], 'bounds': [[0.2, 1.0], [0.5,
     3.0], [1.0, 20.0], [0.125, 1.0], [0.1, 5.0]]}
[34]: import copy
      _lookup = copy.deepcopy(lookup)
      _lduid = copy.deepcopy(lduid)
      for i, uid in reversed(list(enumerate(lookup[0]))):
          ld = lduid[uid]
          if ld.get("failed", False):
              print (uid, "failed", ld["failed_condition"])
              del lduid[uid]
              del _lookup[1][uid]
              del _lookup[0][i]
```

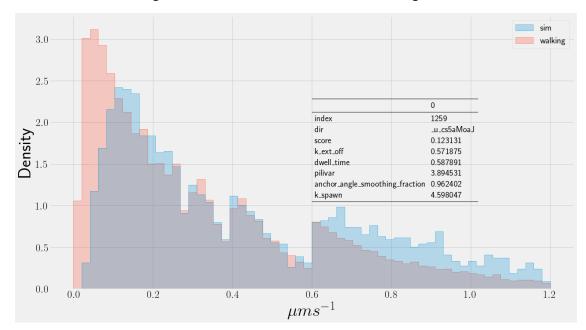
\_u\_PYa0hZ5U failed step\_condition

\_u\_ur0snpU4 failed step\_condition

```
[35]: print(len(_lookup[0]), len(_lookup[1]), len(_lduid))
     7166 7166 7166
[36]: scores = ['fanjin.%s.ks statistic' % subset for subset in reference idx.keys()]
     Yf = sobol.collect_obs(_lookup, _lduid, subsets, scores)
     sortdf = sortscore(problem, _lookup, Yf, scores)
     sortdf["walking"]
           index
[36]:
                                  score k_ext_off dwell_time
                                                                 pilivar \
                          dir
     0
            1259
                  _u_cs5aMoaJ 0.123131
                                          0.571875
                                                     0.587891
                                                                3.894531
     1
             886
                  _u_aYbIpLLa 0.130146
                                          0.606250
                                                     0.910156
                                                                2.039062
     2
            3890
                  _u_Z1UINEcH 0.135629
                                          0.489844
                                                     1.010254
                                                                2.206055
     3
            3739
                  u mN3rQZx8 0.136050
                                          0.777344
                                                     0.736816
                                                                2.243164
                  _u_WABi2BpQ 0.142264
     4
            1260
                                          0.678125
                                                     0.587891
                                                                3.894531
            3227
                  _u_Oqeg5VyP 0.684948
                                          0.364063
                                                     2.965820 17.958984
     7161
     7162
            1325
                  0.821875
                                                     2.619141 17.253906
     7163
            5186
                  _u_j1lsIOpn 0.685121
                                          0.211719
                                                     2.602051 19.499023
            3229
                  _u_9VPkQBTJ
                                                     2.965820 15.435547
     7164
                               0.685987
                                          0.864062
     7165
                  _u_StEhhyce 0.686507
                                          0.200000
                                                     0.500000
                                                               1.000000
           anchor_angle_smoothing_fraction
                                            k_spawn
     0
                                  0.962402 4.598047
     1
                                  0.924805 4.885156
     2
                                  0.896606 3.186426
     3
                                  0.964966 3.109863
     4
                                  0.962402 4.598047
     7161
                                  0.769287 4.818164
     7162
                                  0.142090 4.904297
     7163
                                  0.968384 4.698535
     7164
                                  0.769287 4.818164
     7165
                                  0.125000 0.100000
     [7166 rows x 8 columns]
[37]: best = sortdf["walking"].iloc[0]
      _style = copy.deepcopy(histstyle)
     # _style["kde"] = True
     ax = plot_superimposed(best, "walking", simdir, histstyle=_style)
     plt.tight_layout()
     plt.savefig("/home/dan/usb_twitching/notes/sensitivity/best_walking.png")
     print("best simulation at ", join(simdir, best["dir"]))
```

best simulation at

/home/dan/usb\_twitching/run/5bfc8b9/cluster/sobol\_walking/\_u\_cs5aMoaJ



 $best\ simulation\ / home/dan/usb\_twitching/run/5bfc8b9/cluster/sobol\_walking/\_u\_cs5aMoaJ$